Pedestrian Dynamics in Real and Simulated World

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Abstract: The paper examines the knowledge of pedestrian movements, both in real scenarios, and from more recent years, in the virtual simulation realm. Aiming to verify whether it is possible to learn from the study of virtual environments how people will behave in real environments, it is vital to understand what is already known about behavior in real environments. Besides the walking interaction among pedestrians, the interaction between pedestrians and the built environment in which they are walking also have greatest relevance. Force-based models were compared with the other three major microscopic models of pedestrian simulation to demonstrate a more realistic and capable heuristic approach is needed for the study of the dynamics of pedestrians. **DOI:** **10.1061/(ASCE)UP.1943-5444.0000232.** *© 2014 American Society of Civil Engineers.*

Author keywords: Pedestrian dynamics; Models; Simulation.

Introduction

As cities becomes more densely populated there is increasing interest in predicting and understanding fine scale pedestrian movement to help plan urban areas and design more effective transport infrastructure (Penn and Turner 2002; Fuerstenberg et al. 2002; Daamen and Hoogendoorn 2003; Hoogendoorn and Bovy 2004; Teknomo and Gerilla 2005). Pedestrian facilities need to be efficient, comfortable, and safe in both built environments and transportation hubs, such as shopping malls, theaters, hospitals, and airports. There are studies on architecture design regarding the social use of space (Penn and Turner 2002), which include people in the plan and test whether humans will be comfortable living and moving within the designed or created objects and on traffic regarding the interactions between pedestrian and cars (Retting et al. 2003; Shankar et al. 2003). The movement of large amounts of people in many situations also needs to be concerned, for example stadium in an emergency, or the evacuation of a building. From the point of view of pedestrian dynamics and evacuation, there is the more specific question of how a shifting and moving ground can be included in large area evacuation modeling (Ratner and Brogan 2005). Pedestrian movement in general is becoming a more important topic that is worth extensive scientific inquiry.

Because of the demand of studying pedestrians in the fields of urban and transportation planning, pedestrian modeling, and simulation is imperative. Pedestrians interact continuously with each other and their surrounding facilities, which differ from vehicles that all run in one way on roads and cannot behave random walking patterns. To represent complex pedestrian movements, various models have been proposed. As shown in Fig. 1, in the research fields of built environment, architecture and geography, there are pedestrian dynamics, multiagent pedestrian models and some others which involve the modeling of people's movements. Pedestrian dynamics aim to simulate certain aspects of pedestrian movement in specific situations, such as high density crowding.

There is an increasing importance placed on the consideration of the pedestrian experience in built environment and architectural design. Attractive appearance does not equal high efficiency in facilitating pedestrian flow; neat and ordered pathways or corridors may not cater for pedestrian walking experiences (Moussaid et al. 2009). Typically, in emergency conditions, pedestrian flow would change dramatically to abnormal motion, such as stop-and-go waves and crowd turbulence (Helbing et al. 2001), which may cause serious trampling accidents. In this regard, it is crucial for pedestrian flow motion to be utilized to formulate a new urban design for safety considerations. Meanwhile, there is a great potential to carry out *crash tests* in emergency conditions for a proposed designed urban environment, where pedestrians are injected and flow motion can be simulated and observed. Therefore, to accurately analyze pedestrian movement in the built environment, it is necessary to better understand how the built environment is used by people and the local interaction laws underlying pedestrian dynamics.

On the other hand, pedestrian movement research partly arises from the study and design of modern transportation systems, featuring a mix of automobiles, motorcycles, bicycles, and pedestrians on constructed pathways. Environmental impacts and mobility for nondrivers are becoming important for transportation planning recently. Shinar (1978, 2007) studied in very detail manure around drivers' behavior and addressed methodologies relating to human factors and traffic safety, and recently studied pedestrian behavior and safety measures for pedestrians at urban areas. Mohammed (2001) and Avineri et al. (2012) studied safety issues around pedestrians' behavior at pedestrian crossings.

Environmental analysis, community involvement and nonmotorized planning are also added in transportation evaluation (Litman 2012). Transportation planning has become more multimodal and comprehensive, considering various modes (e.g., walking, cycling, automobile, public transit) and connections among modes. Pedestrians are an integral component of the transportation system. Their movements influence the design and operation of transportation terminals and the timing of traffic signals. In recent years, there have been several attempts to model pedestrian flow. For example, Smith et al. (1995) modeled thousands of people's commuting behaviors in a city, where virtual traffic jams were observed and predicted. The model city in this case was populated with commuters according to detailed demographics and other data

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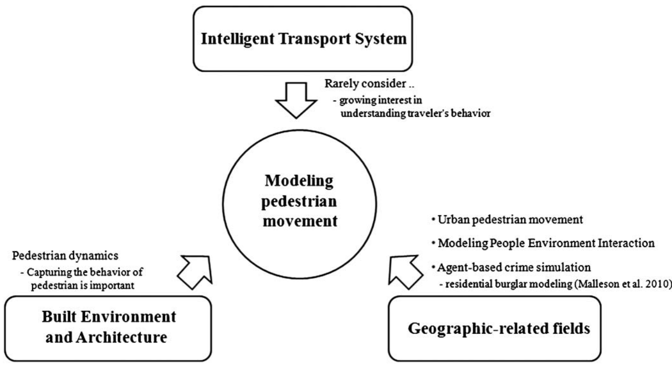


Fig. 1. Pedestrian movement research fields

available to the modelers. The model showed how different plans of the current population of commuters were likely to produce congestion and other effects. The purpose of such a transportation system study is to predict traffic conditions and to guide transportation system design. In nonvehicle pedestrian movement studies, methods derived from vehicle-based transportation systems have generated numerous applications and offered fruitful insights. Blue and Adler (2001) have applied cellular automata (CA) microsimulation to model uni- and bipedestrian directional walkways and demonstrated that these models produce acceptable fundamental flow patterns. Hoogendoorn and Bovy (2004) have developed a model of pedestrian flows based on a gas-kinetic modeling paradigm widely applied for modeling vehicle flows. Gipps (1985), AlGahdi and Mahmassani (1991), Lovas et al. (1994), Helbing and Molnar (1995) and Li (2000) are among others who have worked toward developing pedestrian flow models. However, it is widely believed that vehicles and pedestrians behave differently in terms of speed control, obstacle avoidance and route choice in environments, thus exhibiting distinctive overall performance.

Pedestrian movement is a primary concern for fields ranging from retail, urban planning and design, transportation safety, event planning, security, and other geographical sciences like spatial cognition (Torrens 2012). For most of these fields, the spatial layout and configuration of an environment is an integral part of the planning process that has a direct impact on the movement and behavior of pedestrians. More recent efforts have focused on dynamic modeling at the individual level to provide insight into the larger patterns of movement. Whereas static models can provide parameters that give an indication of possible patterns and areas of concern, a dynamic model can provide a better picture of change over time and can be customized to run scenarios and test hypotheses (Castle and Crooks 2006). Most models to simulate and model pedestrian movement can be distinguished on the basis of geographical scale, from the microscale movement of obstacle avoidance, through the mesoscale of individuals planning multistop shopping trips, to the macroscale of overall flow of masses of people between places. In the *STREETS* model (Schelhorn et al. 1999), for instance, each entity in the model represents a single pedestrian. *STREETS* was built to enable the integration of various scales of movement in a modular way, and could incorporate any previous pedestrian models. Pedestrian activity has two distinct components, namely, the configuration of the street network and the location of building attractors (such as shops, offices, public buildings) on that network. Although the *STREETS* model is close in approach to *TRANSIMS* (Smith 1995), it takes as its subject the activities of pedestrians in subregional, urban districts. However, *STREETS* does not claim to imitate the cognitive behavior of pedestrians, much less represent any particular psychological model of movement. *STREETS* assigns socioeconomic attributes to pedestrians in the first stage, calculates the routes and provides each pedestrian entity with *history* which encapsulates both long-term trends and short-term trends. A more realistic visualization would be possible to develop modules that interact with pedestrian avatars to control the representation of physical movement in an urban space, such as the street network in this case.

This paper firstly discusses the significance of taking into account people's behavior in the built environment. Recent work investigates pedestrian behavior in real circumstances, and asks whether virtual environments can be considered adequate tools to investigate this phenomenon. Next, in reviewing pedestrian walking in the real world, different methods of assessing pedestrian walking are presented and assessed. A series of pedestrian walking experiments conducted in a virtual environment are then discussed, highlighting factors that led to a series of publications that investigate the effect of forced-based components (attractors, expel and bond effects) upon walking. Finally, a number of studies attempting to compare real and virtual pedestrian walking behavior are compared. Research works that focus on the effect of the environment on route formation mechanisms are then reviewed and their methods discussed. Rather than basic walking behavior, it is the mental preference of the pedestrian that is being analyzed. Mental preference primarily refers to the mechanism which controls waking speeds and routing decisions of pedestrians. Assumptions of equivalence (that real walking correlates to virtual walking) are made based solely on this.

Pedestrian simulation is an important approach to understand and analyze human movement. In a broad categorization, pedestrian simulation can be divided into macroscopic simulation and microscopic simulation, in terms of the philosophies of the methodologies

Macroscopic Models

The major activity of human movement in built environments is walking or travelling through buildings or urban areas. Overall, it more or less like a fluid flow as a consequence of fluid molecules moving from one cross-section to another. Pedestrian flow is a result of the movement of many individuals. This is a simple definition of a macroscopic approach to analyzing pedestrian flow.

The macroscopic approach focuses on crowd behaviors as a whole. The characteristics of individual pedestrians are thought to be irrelevant to the overall motion flow. Pedestrians can be represented as particles in the model. Hankin and Wright (1958) measured flow, taking into account that flow in a walkway is affected by what is happening on either side of the section under consideration, and obtained results in Fig. 2. Although they predicted a formation of the arches, which might be formed approximately inversely proportional to the square of the exit width, analysis of pedestrian flow were not concrete and sufficient. Lovas (1994) introduced the basic phenomenon of pedestrian movement, but practical applications were not fairly mentioned. The average flow was represented as:

$$F = S \cdot D \tag{1}$$

where F is the average flow, denoting numbers of people (P) per meter second (P/ms); S (m/s) is the average walking speed and D (P/m^2) is the average density. Illustration of the scenario described by Eqs. (2)–(1) is shown in Fig. 3.

Meaningful results can be obtained through statistics of pedestrians dwelling at different spots, such as process-based research concerns densities at different locations inside large buildings

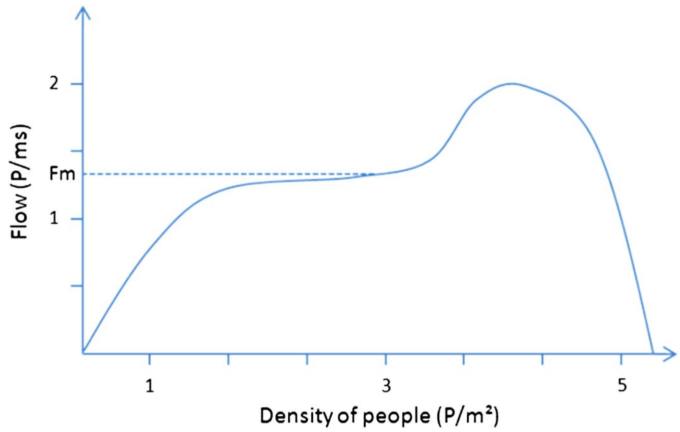


Fig. 2. Graph of people flow density [data from Hankin and Wright (1958)]

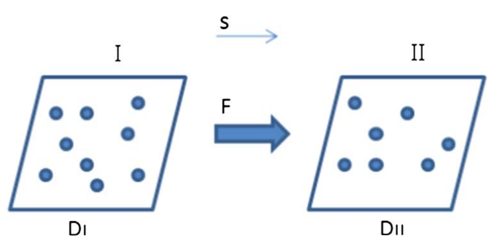


Fig. 3. People flow equation (reprinted from Transportation Research Part B: Methodological, Vol. 28, Gunnar G. Løvås, Lovas, Modeling and simulation of pedestrian traffic flow, 429–443, 1994, with permission from Elsevier)

such as religious places (AlGadhi and Mahmassani 1991), subway stations (Daamen 2004) and airports (Ju et al. 2007). Also, more precise physical and psychological factors can be taken into account by referring to intense crowd movement behavior in a dense pathway in a short period of time. For example, with a fixed width exit, how long does it take to evacuate a certain number of people? An example is given in Fig. 4. However, the applications were limited.

Fields that suit the pedestrian flow are public spaces where crowds are likely to gather, especially in the location of evacuation routes. Physical aspects of built environments are the concern for studying pedestrian flow. Basically, aiming to observe human movement in particular places, the pathways and corridors are first located to represent route trajectories where pedestrians are constrained and walk along (Seneviratne 1989; Kretz et al. 2006). In many buildings such as offices, schools and hospitals, pedestrian flow is constrained to corridors, and pedestrians have little or no choice about the route they take between a particular origin and destination. In shopping malls or plazas, however, objects such as benches, fountains and kiosks or display stands frequently prevent pedestrians from following straight lines between their origins and destinations.

Physical Characteristics of Pedestrians

Besides involving physical aspects of built environments, the physical characteristics of pedestrians need to be considered in models as well. Fruin (1972) found that the fully clothed dimensions of the 95th percentile of the population (95% are less than this) are 33 cm in body depth and 58 cm in shoulder breadth. The average male human body occupies an area of approximately 0.14 m^2. These figures could be helpful in determining the *buffer zone* between pedestrians required for comfortable use of a walkway. Fruin (1972) also reported that behavioral experiments involving personal space preferences showed minimum desirable occupancies ranging between 0.47 and 0.93 m^2 per person, where physical contact with others is avoidable. People require a lateral space of 71–76 cm for comfortable movement. The longitudinal spacing for walking would be 2.5–3 m. This results in a minimum personal area of $1.9 - 0.8$ m^2 per person for relatively unimpeded walking in groups on level surfaces. Individual area occupancies of at least 3.3 m^2 per person are required for pedestrians to attain normal walking speeds and to avoid conflict with others. In addition, Fruin (1972) found that unimpeded walking speed varies between 46 and 107 m per min, and the average is 82 m per min.

Fruin (1972) defined two types of queues: the linear/ordered queue, in which pedestrians line up and are served in their order of arrival; and the undisciplined or bulk queue, where there is more general, less ordered crowding. Fruin (1972) also stated that spacing between people in linear queues is generally 48–50 cm; the recommended lateral single file width for railings or other dividers is 76 cm.

Routing Dynamics of Pedestrians

Although the behavior of pedestrians in the urban environment is sometimes stochastic and unpredictable, especially for crowds, there is good reason to believe it is governed by simple rules. At first glance, molecules in a liquid are presumed to epitomize the behavior of people in a crowd, because they all behave in more

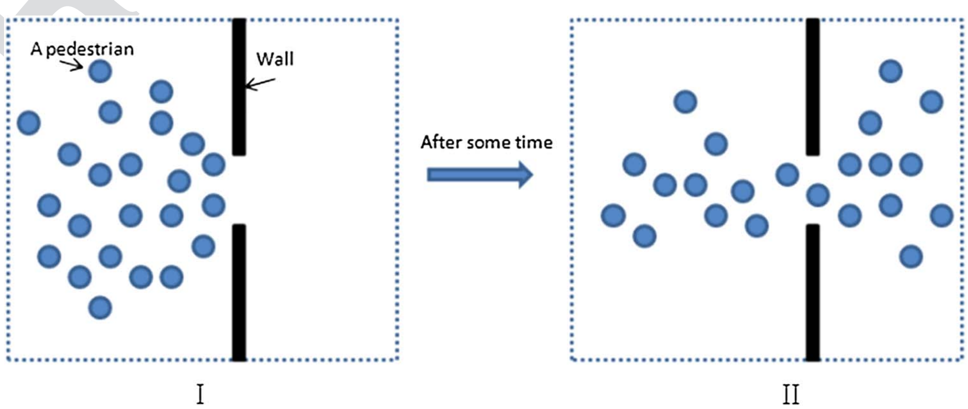


Fig. 4. Illustration of pedestrians evacuating a fixed wide exit [data from Helbing and Molnar (1995)]

or less the same way. Ciolek (1978) stated that pedestrian routes usually fulfill the following criteria:

1. The route is the shortest one connecting the point of departure with the point of destination,
2. The route should avoid physical objects or stationary groups of people,
3. The route should not involve sharp and rapid changes in direction,
4. The adopted route is the quickest and most convenient one to use,
5. The route should not lead across areas where it is difficult to walk,
6. The selected route should not involve rapid changes in elevation of the walking surface, especially for older people and those with luggage or pushing prams,
7. The route is likely to provide interest such as shop windows, and
8. The importance of the location of the route in relation to the nearness of curbs and walls.

Existing models of crowd behavior tried to predict how a crowd will behave (Lovas 1994; Hughes 2003; Ali and Shah 2008). They treat moving masses of humanity as though they were fluids. However, this approach usually cannot predict dynamics when pedestrian flow increases and becomes chaotic. There is a need to treat people as if they were truly human beings who can actively sense the environment, instead of treating them as molecules. In a desired approach, a pedestrian should be able to chart a path to a destination, such as an exit or the end of a corridor, while avoiding obstacles, including other pedestrians (Moussaid et al. 2009). The pedestrian could also make decisions according to some predefined rules. For example, he/she may possess a walking-speed variable and can adjust his/her speed according to his/her distance from such obstacles. All this can be realized by a computer model. Observations of pedestrian speed, density, and flow relations have been carried out in previous studies (Fruin 1972). Mōri and Tsukaguchi (1987) added a relation between speed and density as shown in Fig. 5. Pedestrian area (m^2 per ped) was used instead of pedestrian density (peds per m^2).

Fig. 5 shows that speed is approximately 1.5 m/ sec for free-flow, decreasing gradually to a density of 1.5 peds/m^2, where the relation between pedestrian speed and density is shown as

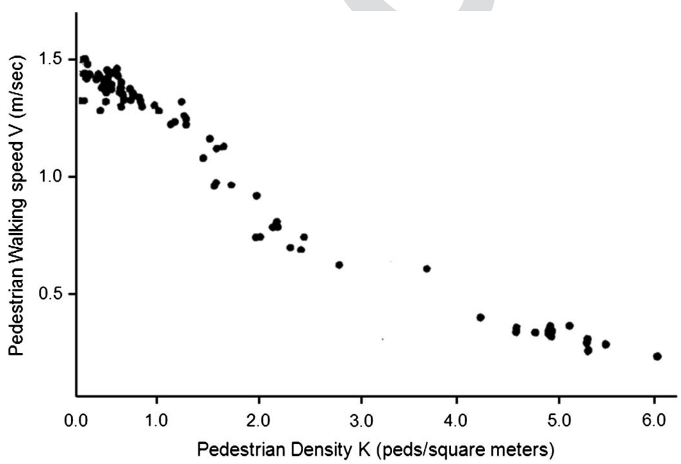


Fig. 5. Pedestrian walking speed and density (reprinted from Transportation Research Part A: General, Vol. 21, Masamitsu Mōri and Hiroshi Tsukaguchi, a new method for evaluation of level of service in pedestrian facilities, 223–234, 1987, with permission from Elsevier)

$$V = -0.204K + 1.48 \tag{2}$$

after which speed drops sharply.

Because a pedestrian cannot necessarily see his final destination from his starting point, and may in any case choose to deviate from a direct path, route selection is based around the concept of intermediate destinations (or nodes) generated by the objects in the open area. Gipps and Marksjo (1985) used the physical layout to generate a number of nodes in their model. A pedestrian walking between his origin and destination moves from one node to another. When he is within a short distance of the node to which he is walking, he has to make a decision about the following node. The choice is limited by the requirement that the next node must not be hidden from his/her present position by a fixed obstacle. That is, a straight line between the present node and the next does not intersect any obstacle. Besides physically accessible quality factors, various soft factors or social forces can also lead to either attracting or repelling pedestrian to parts of the network and influencing their routing decisions. These factors have in common that prior knowledge must be available to the individual pedestrian about their character and location (Czogalla and Herrmann 2011). If these soft factors exist temporarily, an influence on a routing decision can only be assumed if it is visible to the individual at the point of decision. Examples of attractions are possibilities of social interaction such as groups of persons, street artists, street markets, and temporary exhibitions or street festivals. Examples of repelling factors are socially insecure places such as known crime spots and areas known for loitering and begging, and alcohol and drug abuse. Czogalla and Herrmann (2011) indicated that the valuation of soft factors, as an increase or decrease of the pedestrian quality attribute (PQA), can be realized by estimating the social force factor a_{SF} for each concerned network element. The domain of a_{SF} is defined as:

$$-1 < a_{\mathrm{SF}} < 1 \tag{3}$$

valued from repulsion (−1) to attraction (1). The social force factor a_{SF} is added to the evaluated link related PQA. As such, the social force factor serves as an additive measure for the further increase or decrease of the virtual distance between nodes of the network:

$$\text{walkability attribute} = \frac{1}{2}(\mathrm{PQA} + a_{\mathrm{SF}}) \tag{4}$$

The resulting attribute is denoted as the walkability attribute and measures the cost for traveling the network paths. Decisions for route choice are drawn during the routing process that determines the shortest virtual path.

The walkability attribute defines a measure for the virtual distance that is essential for a routing decision that takes into account the link quality and social factors. In the process of utility maximization which is presumed as a basis for the routing decision, always the shortest virtual distance will be chosen by the pedestrian.

Apart from quality-related factors, there are important human factors that will have a strong impact on routing decisions at the tactical level. The trip purpose, personal fitness, and time constraints will have a significant influence on route choices. It is expected that these factors will not change during a trip. Hence, the individual factors are considered as additional input quantities for the utility maximization process of route choice that will influence the decisions evenly over the entire network.

Limitation of Macroscopic Models

Particle representation theory is a good way to evaluate macro outcomes of pedestrian flows; for example, the total number of pedestrians who occupy a corridor or a building space. However, if more detailed information is required, such as how pedestrians react in a crowd or how pedestrians' interactions with building facilities impact on macro flow, the notion of pedestrian flow could be less useful.

The ability to predict the response of a pedestrian to the behavior of his neighbors in a corridor or an open area is important in estimating the effect of changes in the walking environment (Greenwald 2001; Landis 2001; Saelens et al. 2003). Whereas objects provide foci of interest around which people are likely to congregate, though talking or watching the passing traffic, they also involve pedestrians in a choice of route. From the viewpoint of management of such facilities, these objects fulfil a useful role in reducing the speed of pedestrians and dispersing them, as pedestrians who walk too quickly are unlikely to be attracted by window displays. If there are too many impediments in corridors, the mall may be unable to handle the crowds at times of peak usage. Thus, controlling pedestrian movements within and around buildings is an important facet of design.

In this regard, there exists a research opportunity to investigate the interactions among pedestrians and ambient environments so as to understand how a built environment impacts on pedestrian flow. For designers of buildings and other constructed facilities, it appears to be important to be able to predict how changes in the walking environment will affect the pedestrian flow. These changes can act on an individual pedestrian directly by diverting him/her from their preferred route, and indirectly through their effect on other pedestrians.

Although the ability to predict pedestrian flows within and around constructed facilities is important, existing macroscopic models of pedestrian flow are, in the most part, limited to the quasi-steady state flow in corridors (Fruin 1972). However, many buildings have pedestrian flows that are transient and vary over relatively short time intervals. Such variations in flows can arise from events such as a lift disgorging its passengers, or a set of traffic signals outside the building allowing pedestrians to cross the road and enter the building. Consequently, it is desirable to be able to model the behavior of pedestrians in more detail than is provided by macroscopic models.

Microscopic Models

Pedestrian flow is categorized into macroscale and microscale perspectives. Microscopic approaches separately concentrate on each individual's behavior. The term *microscopic* here refers to the philosophy of the methodology rather than attributes of problems. It does not mean that microscopic approaches can be totally distinguished from macroscopic approaches in terms of applications. Normally, when pedestrians walk free of congestion in a sparse environment, the macroscale side is more informative; when passengers aggregate into dense crowds, the microscale side is more determinative for integral performance (Xu and Duh 2010).

A microscopic approach treats each individual as an independent entity which consists of multiple traits. Microscopic models have been evolving since the development of a pedestrian model based on fluid dynamics (Helbing 1992). Later, some models of crowd behaviors were developed (Helbing and Molnar 1995; Batty et al. 1999), and closely matched various observed pedestrian behaviors. In such models, pedestrians can spontaneously form lanes, for the purpose of avoiding collisions and quick movement.

Microscopic analysis has been made possible by the rapidly increasing speed of computation. A microscopic simulation of a microscale pedestrian flow problem is often computationally intensive. Pedestrian flow is loose and free, and is more complex than vehicular flow which is constrained by *lanes* (Jian et al. 2005). From the standpoint of general principles for modeling, human flow is a complicated system, consisting of sets of interacting elements, namely, people. Performing a microsimulation of pedestrian movements is a simple way to handle the stochastic nature of such pedestrian flows (Kholshevnikov et al. 2008). A microscopic pedestrian simulation model is a computer simulation model of pedestrian movement where every pedestrian in the model is treated individually (Teknomo et al. 2000).

Micro Models of Pedestrian Dynamics

Pedestrian flow involves both the physical and the behavioral characteristics of crowds. It is perceived as a typical complex system (Helbing et al. 2001). Physical laws alone are considered insufficient to represent pedestrian walking dynamics. Therefore, experts from physics, applied mathematics, psychology, sociology, and transportation engineering have been working on different aspects of the problem (Kholshevnikov et al. 2008).

The distinction among models of pedestrian behavior noted by Haklay et al. (2001) is determined by limited local information (reactive), or by overall knowledge of global outcomes (cognitive). In previous models most of the cognitive work done by agents occurs outside the dynamic part of the model. It can be argued people know the overall purpose of their trip before they do it, but some may plan as they go along, and pedestrians who are unfamiliar with an area may have no plans other than to explore, but adapt their behavior as they become more familiar with the environment. Ward (2005) devised the *JPed* model which allows both cognitive and reactive behavior to be modeled together in the dynamic stage of simulation. The cognitive mechanism of the modeled pedestrian has not yet studied in detail, such as how pedestrian behave wayfinding and communicate with each other when they are walking through a built environment. Regarding to fields of urban planning, the spatial layout and configuration of an environment is an integral part of the planning process that has a direct impact on the movement and behavior of pedestrians.

Pedestrian dynamics has not been studied as extensively as vehicular traffic owing to the very nature of pedestrian walking. It is always unpredictable about walking routes and a sense of random speeds of pedestrian walking. Unlike vehicular traffic, pedestrians can stop and change their directions suddenly without a significant slowdown process. Although the speeds of pedestrian walking can be concluded through the statistics of surveys and inspections, it is also difficult to verify correct walking speeds in simulation. In terms of modeling large population of pedestrians in urban environments, pedestrians are always treated as particles subjects to certain interaction rules with obstacles of the urban environments and other pedestrians. There are generally five models in modeling pedestrian dynamics.

Microscopic pedestrian flow models include the benefit-cost cellular model (Gipps and Marksjo 1985), cellular automata model (Blue and Adler 1999; Dijkstra et al. 2000), magnetic force model (Okazaki 1979), social force model (Helbing et al. 1995), and models derived from other mature technologies such as game theory (Lo et al. 2006) (Fig. 6). If the behavior of individuals can be adequately modeled, and the appropriate distribution of pedestrian types is employed, their combined behavior would be realistic.

The benefit-cost cellular model focused on the interactions between pedestrians which were intended to be used in graphical computer simulation. It simulated the pedestrian as a particle in a cell. The program used interactive color graphics to display the operation of the model and assist in the validation and verification of

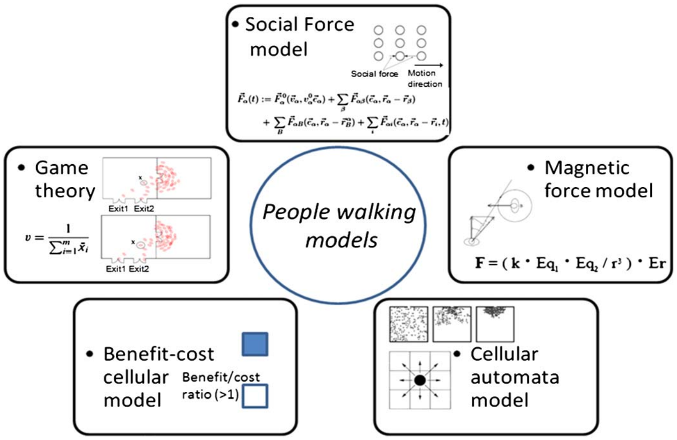


Fig. 6. Current pedestrian walking models

the model. However, the model is limited by restricted computation capacity and, as a result, is not suitable for practical purposes.

To realize the interactions of pedestrians, pedestrians should be of a number of different types, and it should be possible to change their characteristics and numbers to suit the situation being investigated. The parameters in the model should correspond to obvious characteristics of pedestrians whenever possible (Gipps and Marksjo 1985). However, little work has been done to conclude pedestrian characteristics until now. On the one hand, urban environments and building facilities are varied. It seems impossible to have a set of identical characteristics of pedestrians for all contexts. On the other hand, the interaction functions which link pedestrian characteristics and the action responses regarding the built environment are sophisticated.

In terms of the repulsive effect among pedestrians and obstacles, Gipps and Marksjo (1985) used simple arbitrary scores to assign cell occupation, which evidently lost physical meaning. To improve this, Okazaki and Matsushita (1993) developed the magnetic force model to apply to pedestrian movement. Each pedestrian and obstacle has a positive pole. The negative pole is assumed to be located at the goal of the pedestrian. Thus, the intensity of the magnetic load of a pedestrian and the distance between pedestrians bring about the magnetic force which leads pedestrians to move to their goals. Pedestrians move their goals and avoid collisions. Every pedestrian applies two forces: one is a magnetic force, which is assumed to be dependent on the intensity of the magnetic load of pedestrian and distance between pedestrians; the other one acts on a pedestrian to avoid collisions with other pedestrians or obstacles. As a consequence, it will exert acceleration. Although the model involves certain physical meanings of real pedestrian movement, it still deviates from the true sense to some extent.

The cellular automata model is able to model pedestrians (Burstedde 2001). In this model, space, time, and state are discrete. The walkway is modeled as grid cells. Each pedestrian can only occupy one cell at a time, and at the next time the pedestrian will either move to or leave a cell. The occupancy of a cell is governed by localized neighborhood rules. The movements of a pedestrian are lane changing and cell hopping. Although it is effective enough to estimate the probability that a certain direction and place will be chosen as a destination, the model cannot deal with each pedestrian movement in a more fine-scale environment. Pedestrian models which can be applied to the erratic movements of users in multipurpose spaces, such as shopping malls and airport terminals, are strongly needed.

Helbing et al. (1991–1999) developed the social force model which supposes a pedestrian is subjected to social forces that motivate the pedestrian. The model is based on the assumption that every pedestrian has the intention to reach a certain destination at a certain target time. The direction is a unit vector from a particular location to the destination point. The ideal speed is equal to the remaining distance per remaining time. It is the most popular microscopic pedestrian model up to now and has been implemented in many specific pedestrian simulations (Seyfried 2005; Xu and Duh 2010). However, like the other two microscopic pedestrian simulation models reviewed above, there is no statistical guarantee that the parameters would be feasible for general cases.

Besides the above models, a queuing network model is also used in microscopic pedestrian simulation (Watts 1987; Lovas 1994; Thompson and Marchant 1995). The approach is a discrete-event Monte Carlo simulation. It suggested that each room is denoted as a node and the doors between rooms are links. Each person departs from one node, queues in a link and arrives at another node. A lot of pedestrians move from one node to another in search of the exit door. In one evacuation model, all people have to move from their present position to an exit as quickly and safely as possible. Walking route and evacuation time are recorded in each node. As soon as a pedestrian arrives in a node, it makes a weighted-random choice to choose a link among all possible links. The weight is a function of actual population density in the room, but a pedestrian may have to wait and find another route to follow when the current link cannot be used. In the source node, a pedestrian needs a limited time to react before movement begins, whereas in the final destination node it will stop.

The research in the present thesis considers pedestrian flow in normal conditions within airport terminals, so the sense of the reality of passenger flow is critical. In contrast with these microscopic models, the social force model is the most suitable for the research, because its variables have concrete physical meaning and can be explicitly measured. The variables in the social force model can also be easily adapted to real passenger walking behaviors. Table 1 gives a comparison of four applicable microscopic pedestrian simulation models. The other two are not sophisticated enough for the research in this thesis, either because of low capability (as in the benefit-cost cellular model) or because it is not applicable (game theory). Because the proposed passenger flows in an airport terminal will be envisaged by emergent phenomena of autonomous individual passenger behaviors, only the social force model meets the needs of the research.

Nevertheless, Moussaid et al. (2011) also indicated that cognitive, heuristics-based models in pedestrian simulation have the potential to replace conventional physics and force-based models. This approach seems to be especially suitable for high density situations as, for example, the crowd disaster in Duisburg, Germany, and other similar mass events. Technically, this is done by introducing a contact force that becomes active and effective in dense situations. The new heuristic approach is based on the vision dynamics of pedestrians—and in this way on the proactive behavior—in contrast to physics-based models where pedestrians are passively influenced by forces. However, at this stage, this proposal is not yet proven to be able to intuitively capture collective pedestrian behaviors such as lane formation and dynamics in high density situations, although it seems very promising according to first results and validations.

Social Force Model

Based on the comparison of the models (Table 1), the social force model is very well suited for modeling pedestrian flow in the

Table 1. Comparison of Microscopic Pedestrian Simulation Models

	Features	Cellular automata	Magnetic force	Queuing network	Social force
T1:1	Features	Cellular automata	Magnetic force	Queuing network	Social force
T1:2	Movement to goal	Min (gap, max speed)	Positive (negative) magnetic force	Weighted random choice	Intended velocity
T1:3	Repulsive	Gap or occupied cell	Positive and negative magnetic forces	Priority rule	Interaction forces
T1:4	Value of the variables	Binary	Arbitrary score	Physical meaning	Physical meaning
T1:5	Higher programming orientation in	If-then rules (heuristic)	Heuristic	Queuing model	Dynamical system (continuous)
T1:6	Phenomena explained	Macroscopic	Queuing, way finding in maze	Queuing, evacuation	Queuing, self-organization

microscopic aspect. The social force model provides easy adaptation of real passenger behaviors. In this regard, it is envisaged that a newly devised model of pedestrian walking dynamics can utilize the social force model as a basic pedestrian walking model and then build its own tactical dynamic model for routing dynamics. In addition, because the social force model is restricted to walking interactions of pedestrians, it suits models based on other new physical built environments.

The mechanisms and capability of the social force model are provided in detail. Helbing et al. (2001) indicate that pedestrians can move freely only at small pedestrian densities, otherwise their motion is affected by repulsive interactions with other pedestrians, giving rise to the self-organization phenomenon. They believed that the dynamics of pedestrian crowds are predictable, although pedestrians have individual preferences, aims and destinations. Because human behavior is *chaotic* or at least very irregular, many have pointed out that individuals will usually not take complicated decisions in standard situations between various possible alternative behaviors, but apply an optimized behavioral strategy, which has been learned over time by trial and error. Therefore, a pedestrian will react to obstacles and other pedestrians in an automatic way.

The optimal pedestrian behavior can be in principle determined by simulating the learning behavior of pedestrians, which indicates pedestrians' parameters can be changed randomly in the simulation, and the inverse travel times and the collision rates with different behavioral strategies can be compared with each other. Once successful strategies are replicated, they will be further refined over time. After several time cycles, it yields a parameter set which does not change anymore. The parameter set finally determines the optimal pedestrian behavior in terms of interaction strength, acceleration behavior, and path choosing. Helbing (1995) also developed an approach to modeling behavioral changes and put it into mathematical terms.

As the position of the pedestrian α can be represented by points $r_\alpha(t)$ in space, which change continuously over time, pedestrian dynamics can be described by the following equation of motion:

$$\frac{dr_\alpha(t)}{dt} = \nu_\alpha(t) \tag{5}$$

The functions delineating the temporal changes of the actual pedestrian velocities $\nu_\alpha(t)$ can be interpreted as the driving force of this motion, which are called behavioral forces or social forces.

Fig. 7 shows a simple social force model of pedestrian motion (Helbing and Molnar 1995). There are three force terms in the presented model of pedestrian behavior [Eq. (3)]: There is acceleration towards the desired velocity of motion. A pedestrian keeps a certain distance to other pedestrians and environmental obstacles. A pedestrian is distracted and walks to a specific attractive location.

The resulting equations of the motion are nonlinearly coupled LANGEVIN equations:

$$\overrightarrow{F_\alpha}(t) = \overrightarrow{F_\alpha^0}(\overrightarrow{\nu_\alpha}, \nu_\alpha^0 \overrightarrow{e_\alpha}) + \sum_\beta \overrightarrow{F_{\alpha\beta}}(\overrightarrow{e_\alpha}, \overrightarrow{r_\alpha} - \overrightarrow{r_\beta}) + \sum_B \overrightarrow{F_{\alpha\beta}}(\overrightarrow{e_\alpha}, \overrightarrow{r_\alpha} - \overrightarrow{r_B^\alpha}) + \sum_i \overrightarrow{F_{\alpha i}}(\overrightarrow{e_\alpha}, \overrightarrow{r_\alpha} - \overrightarrow{r_i}, t) \tag{6}$$

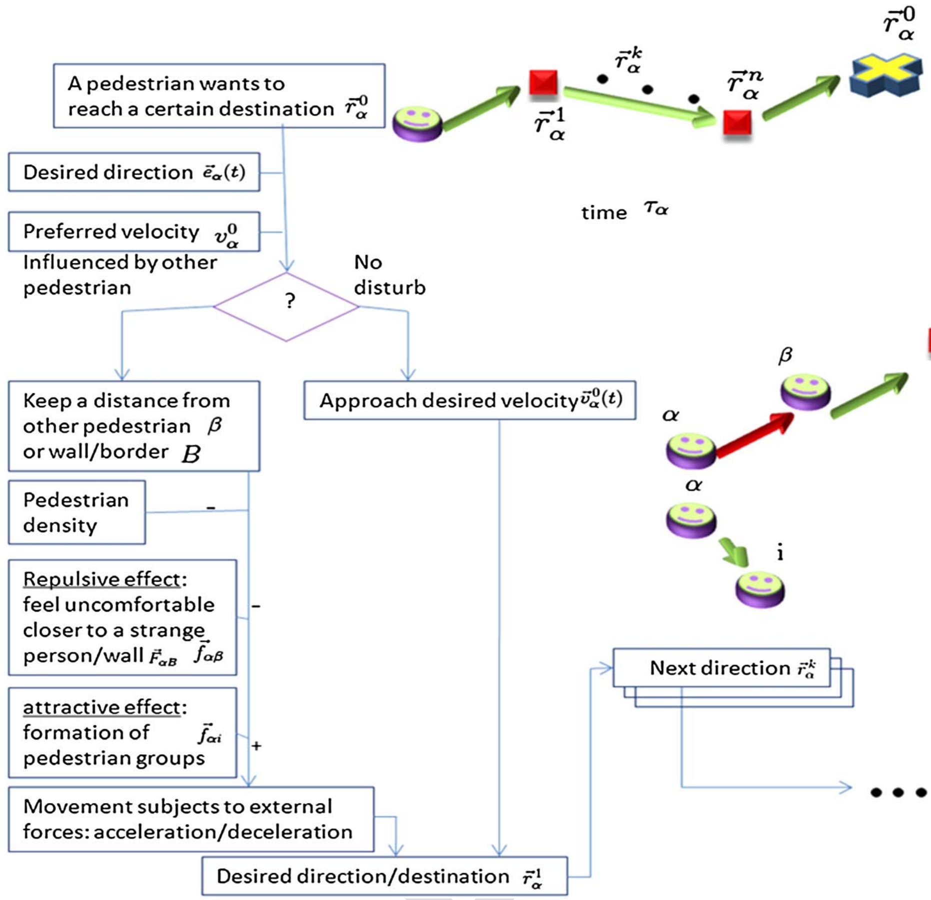
$$\frac{d\overrightarrow{w_\alpha}}{dt} = \overrightarrow{F_\alpha}(t) + \text{fluctuations} \tag{7}$$

where

- α and β stand for two different pedestrians.
- B stands for an environmental obstacle in the model.
- $\overrightarrow{F_\alpha}(t)$ is interpreted as social force,
- $r_\alpha(t)$ represents the actual position of pedestrian α at time t,
- $\overrightarrow{\nu_\alpha}$ is the actual velocity of a pedestrian,
- $\overrightarrow{e_\alpha}$ represents passenger's desired direction,
- $\overrightarrow{\nu_\alpha^0}$ is the desired velocity, which equals to $\nu_\alpha^0 \overrightarrow{e_\alpha}$,
- $\overrightarrow{r_B^\alpha}$ denotes the location of that piece of border B that is nearest to pedestrian α.
- $\overrightarrow{F_{\alpha\beta}}$, $\overrightarrow{F_{\alpha\beta}}$ and $\overrightarrow{F_{\alpha i}}$ represent repulsive effect that a pedestrian interacts with another pedestrian β, a border B and an attractor i.
- $\frac{d\overrightarrow{w_\alpha}}{dt}$ is the systematic temporal changes. It is of the preferred velocity $d\overrightarrow{w_\alpha}$ of a pedestrian α. It is described by a vectorial quantity $\overrightarrow{F_\alpha}(t)$. The fluctuation term considers random variations of the behavior.

The social force model is capable of describing the self-organization of several observed collective effects of pedestrian behavior very realistically. The computer simulations of pedestrian groups not only demonstrate the development of lanes consisting of pedestrians who walk in the same direction, but also discover oscillatory changes of the walking direction at narrow passages. The segregation effects of lane formation are not a result of the initial pedestrian configuration but a consequence of the pedestrians' interactions. Nevertheless, it normally leads to a more effective pedestrian flow because time-consuming avoidance maneuvers occur less frequently. These spatiotemporal patterns arise owing to nonlinear interactions of pedestrians. They are not the effect of strategic considerations of the individual pedestrians because they were assumed to behave in a rather automatic way.

The social force model can be extended by a model for the route-choice behaviors of pedestrians. As soon as such a computer program is completed it would provide a feasible tool for pedestrian traffic planning. Helbing et al. (2005) used video-based techniques (time-lapse recordings and single-frame analysis) to explore the effects of bottlenecks, obstacles, and intersections. Their evaluations of video-recordings showed that the geometric boundary conditions were not only relevant for the capacity of the elements of pedestrian facilities; they also influence the time gap distribution of pedestrians, indicating the existence of the self-organization phenomenon. Self-organization indicates that these patterns are not



F7:1 **Fig. 7.** Social force model

externally planned, prescribed or organized by, for example, traffic signs, laws or behavioral conventions. Instead, the spatiotemporal patterns emerge attributable to the nonlinear interactions of pedestrians. These interactions are more reactive and subconscious rather than being based on strategic considerations or communication. Early investigations of the self-organization phenomenon in pedestrian crowds are based on qualitative empirical observations and simulation studies (Helbing 1991; Helbing et al. 2001).

The great challenge for simulation models is the reproduction of the observed collective phenomena in pedestrian crowds. This includes lane formation in corridors and oscillations at bottlenecks in normal situations, whereas different kinds of blocked states are produced in panic situations. By means of microsimulations based on a generalized force model of interactive pedestrian dynamics, the spatiotemporal patterns in pedestrian crowds can be successfully reproduced and interpreted as self-organized phenomena. The advantage of the social force-based simulation approach is its simple form and its small number of parameters, which do not need to be calibrated for each new situation. Therefore, the model is suitable for the prediction of pedestrian streams in novel architectures and new situations.

Tactical Routing Models

Pedestrian flow was previously illustrated by representing it in terms of elementary flow models (Hankin and Wright 1958; Lovas 1994), namely, people moving in an orderly fashion in the same direction. Kholshevnikov et al. (2008) addressed the problem that the location of people within pedestrian flows can be quite random and stochastic. The spacing between people is variable. Local congestion occurs and dissipates within different parts of the flow. In their approach, travel speed was defined in terms of an average from data obtained from several sectors in a pedestrian flow when extended over many tens of m. Travel speed in any interval of time, characterized by a particular, random density value depends on a number of factors. In this case, randomness is a characteristic of a real process and hence, in terms of a mathematical description, the relation between travel speed and density is a random function.

The value of the functioning parameter for each person depends on their individual properties (physiological and psychological characteristics of people in the flow) and it changes as interactions between people and common factors occur (emotional state, route type, and physiological reactions). Kholshevnikov et al. (2008) demonstrated, in a changing emergency context, that psychophysics and psychophysiology theory are able to establish rules to link the emotional state of persons to their travel speed and pedestrian flow density. Regarding pedestrian flow in normal conditions, their work did not address these aspects, and there is still much work to be done in terms of considering not only physical influence factors but also psychological aspects.

Czogalla and Herrmann (2011) focused on the modeling of a decision process that takes place at the tactical level of a pedestrian's trip. The tactical level is defined in delimitation to the superior strategic level and subordinated operational level with respect to trip purpose and spatial relations. On the strategic level, the purpose, origin, and destination, the choices for traffic mode and time of departure are set before the trip starts; whereas, on the tactical level, decisions are being made for the actual route or diversions within the pedestrian's network during the trip. At the tactical level, the decision-making process can be modeled by the minimization problem of walking costs in a network that takes into account both the network-related quality and individual-related factors (Czogalla and Herrmann 2011). For the tactical level, that is, on the trip during walking, the decision-making process for route choice can be modeled by minimizing the problem of walking costs that take into account both the network-related quality and individual-related factors. It is assumed under the preconditions of acquired prior knowledge and assessment of the walking network by the pedestrian (Czogalla and Herrmann 2011). Individual factors, such as time constraints and physical abilities, are incorporated in the model as they influence the weight of attributes used in the process of maximizing the personal utility of the human individual.

Agent-Based Pedestrian Models

Agent-based modeling offers a way to model social systems that are composed of agents who interact with and influence each other, learn from their experiences, and adapt their behaviors so they are better suited to their environment. Agent-based modeling is currently applied to model people walking at spatial scales and in city or urban areas.

Deadman (1994) introduced research on people-environment interactions using agent-based models, in which they simulated people deciding on taking a route during recreational trips in forest areas. Batty (2001) indicated that there was a dearth of work on pedestrian movement and introduced an agent-based method in modeling urban pedestrian movements. Teknomo and Gerilla (2005) presented a pedestrian movement model, which used a multiagent system for pedestrian traffic analysis. The model captured the dynamic microscopic interaction between pedestrians, which cannot be addressed using the traditional macroscopic approach. The pedestrians were modeled as autonomous agents with nonlinear system different equations. A critical issue for such multiagent pedestrian models, however, is the validation of the model against real-world data.

Haklay et al. (2001) introduced recent advances and developments in modeling techniques and showcased an agent-based model, namely, the *STREETS* model, developed using the Swarm simulation toolkit and GIS. The *STREETS* model adopted a holistic, agent-based approach to pedestrian simulation, and as a result synthesized existing models and offered a test-bed for synergetic and cumulative influences between those models.

The traditional methods for observing and recording the movement of pedestrians in city streets are basically physical counts and time-lapse photography (Helbing et al. 2001). Gravity or spatial interaction techniques are rarely performed at the level of detail required for the prediction of pedestrian numbers, although they are able to distribute overall flow results across transport networks to predict the intensity of use of different routes. Thus, they are rarely successfully applied to modeling pedestrian movement at the scale of buildings and streets (Kurose et al. 2001). The reasons, to this extent, are the absence of adequate data at the level of detail and the limitation of the modeling capability. They are less applicable at small spatial scales, only suited to model general patterns of movement and can never be used to model the movement of individuals.

The *STREETS* model was initially loaded with pedestrians who have prescribed activity schedules or plans. These pedestrians are then modeled as agents who may choose to change their plans in response to their surroundings and the behavior of other agents. Each agent has characteristics under two broad categories: socioeconomic and behavioral. The socioeconomic characteristics relate to income and gender, and are used to create a planned activity schedule for the agent. With the activity schedule, the agent autonomously decides a route that it intends to take in the model. Many other heuristic methods may also be used in this route planning.

Behavioral characteristics contribute to the detailed behavior of agents. Factors include speed, visual range, and fixation. In the dynamic operation of the model, agents have five programmed control modules to compute local movements. They are the Mover, the Helmsman, the Navigator, the Chooser, and the Planner. Moreover, the more abstract goals of the upper levels can be decomposed to simple actions as control and target variables of the state of agents. All modules can access agent states. However, the *STREETS* model does not claim to imitate the behavior of cognitive movement. So it hardly represents a particular psychological model of movement.

Emergence is generally seen as unidirectional, because agents are autonomous objects. The habitual, patterned, aggregate behaviors are the key drivers of change at more aggregate levels, and it takes time for actors in any socioeconomic setting to recognize the patterns and adjust their individual and collective responses to those patterns. Emergence should be understood as occurring through social action through the cognitive processing of events by individuals over time.

The agent-based modeling approach is highly applicable to the pedestrian dynamics field. It is also clear that the application of socioeconomic and other data to populate agent models with representative populations is viable and promises to enhance the prospects for this modeling approach in built environment planning more generally.

Agent-Based Modeling and Simulation

Agent

Regarding each individual's behaviors, the independent agent approach is feasible to represent each individual pedestrian as an independent pedestrian agent and construct a pedestrian flow model through a bottom-up approach. It is also described as the microscopic approach.

An agent can be thought of as an autonomous, goal-directed software entity. An agent's autonomy is constrained by the fact that it is constructed by human programmers and, in this context, this indicates that it pursues its goals in an open-ended manner. The definitive example of agent-based modeling technology is provided by the Santa Fe Institute's *Swarm* simulation toolkit (Minar et al. 1996). Agents incorporate sophisticated artificial intelligence techniques whereby they learn new ways to attain their goals (O'Sullivan and Haklay 2000). For the proposed pedestrian agent in particular, it is possible for detailed traits of a pedestrian to be modeled. Together with advanced computational technologies, it provides a feasible way to tackle large crowds of pedestrian movement.

An agent-based model could have hundreds of agents or more interacting in an artificial virtual world, which represents a real-world environment. The modeler programs agents with proper rules governing their behavior and examines simulation outcomes to obtain insight into real-world scenarios. It seems evident that built environment planners are well placed to investigate such models in both theoretical and substantive ways, contributing to the development of spatial dynamics in these models, and evaluating the assumptions which underlie them. In this sense, agent-based models of people walking regarding spatiotemporal dynamics are introduced.

Agent-based modeling and simulation is a relatively new approach to modeling complex systems composed of interacting, autonomous agents (Macal 2010). Agents have behaviors, often described by simple rules, and interactions with other agents, which in turn influence their behaviors. By modeling agents individually, the full effects of the diversity that exists among agents in their attributes and behaviors can be observed and give rise to the behavior of the system as a whole. By modeling systems from the ground up—agent-by-agent and interaction-by-interaction—self-organization can often be observed in such models. Patterns, structures and behaviors emerge that were not explicitly programmed into the models, but arise through the agent interactions. The emphasis on modeling the heterogeneity of agents across a population and the emergence of self-organization are two of the distinguishing features of agent-based simulation as compared with other simulation techniques such as discrete-event simulation and system dynamics.

A typical agent-based model has three elements (Macal 2010):

1. A set of agents, their attributes and behaviors.
2. A set of agent relationships and methods of interaction—an underlying topology of connectedness defines how and with whom agents interact.
3. The agents' environment—agents interact with their environment in addition to other agents.

Most often agent-based modeling is used to model systems where outcomes have a high degree of dependency on the actions of humans. Common applications include the spread of diseases or information between populations, people or traffic movements, and the impact of marketing campaigns.

In the nonacademic area, as suggested by the British Airport Association in terms of complex and comprehensive airport systems (de Neufville and Odoni 2003), there are no off-the-shelf tools that could meet all future requirements. Therefore, a skillful and comprehensive modeling solution for future complex airport systems is needed. The outcome of agent-based modeling and simulation for passenger flow could have a promising application.

From the comparison of the common features of the above models, several advantages of agent-based models are concluded:

1. An agent is a discrete entity with its own goals and behaviors; it is also autonomous, with the ability to adapt and modify its behavior.
2. Agent-based models are inclined to perform methodological individualism.
3. This commitment to individualism is accompanied by a one-way notion of emergence: the social can emerge only from the individual.
4. Less behavioral complexity would be preferred; simplicity can help model and understand.

In summary, microscopic pedestrian models can deal with single passengers and allow the study of their interactive tendencies with each other and the neighboring environment.

Agent-Based Model

An agent-based model is one in which the basic unit of activity is the agent. Agents represent actors at the individual level. An agent is an identifiable unit of computer program code which is autonomous and goal-directed (Hayes 1999). An agent is an entity (either computer or human) that is capable of carrying out goals, and is part of a larger community of agents that have mutual influence on each other. Agents may coexist on a single processor, or they may be constructed from physically separate but intercommunicating processors (such as a community of robots) (Hayes 1999). The key concepts in this definition are that agents can act autonomously to some degree, and they are part of a community in which mutual influence occurs (Hayes 1999). The outcomes of the model are determined by the interactions of many agents, usually tens or even thousands. However, physical spatial mobility in many models is not considered at all, because in most agent-based models the main concern is to understand how individual behavior leads to global outcomes in a generic sense, rather than in the modeling of the real world.

A typical agent-based model is composed of agents who interact with each other and also with their environments (Castle et al. 2008). Agent-based models are usually considered as forming a miniature laboratory where the attributes and behaviors of the agents and the environment in which they are housed can be altered. In turn, they can be experimented upon, and the repercussions of such experimentation can be observed over the course of multiple simulation runs.

Agent-based models are good tools for studying the effects on process that operate at multiple scales and organizational levels, because they not only simulate the individual actions of many diverse agents but can also measure the resulting system behavior and outcomes over time (Brown 2006). Basically, agent-based models provide tools to tackle those change ideas which have emerged from complexity science, changing from the aggregate to disaggregate and from the static to the dynamic. It allows exploration of how individual decisions are made and how such decisions lead to emergent structures evolving (Crooks 2009).

Agent-based modeling is derived from complexity science and complex systems. Because the world is increasingly complex, the systems that need to be analyzed are consequently becoming more complex as well, particularly in terms of their interdependencies. Traditional models for some systems are not as applicable as they once were, because many human-made systems have been viewed as complex systems which cannot be adequately modeled by usual methods; large airport systems are a prime example.

Over the last three decades, simulation has become a frequently used modeling tool for supporting studies of complex systems. The simulation modeling paradigms used in this regard can be classified in three groups, as compared in Table 2:

1. System dynamics modeling
2. Discrete-event simulation modeling
3. Agent-based simulation modeling.

Agent-based modeling takes another perspective on simulation. Agent-based modeling is centered on interacting individuals with a view to assessing the system-wide effects of their individual behavior and interactions, rather than system dynamics models which model from an overall picture of the flow in a system. Typically, thinking of a discrete-event simulation model of an airport, passengers are pushed or pulled between check-in and security processes, and it works through to model several aspects of the airport: for example, some passengers might stop at a restaurant/café and then browse a gift/book shop. With an agent-based mindset, however, the passengers are in control and, like in real life, would make their own decisions on where to go and when. Instead of a centralized or global simulation control, agent-based modeling attaches rules of a system to individual agents. In discrete-event simulation, work-items are passive and actions are defined by activities that process them. Therefore, agent-based modeling is particularly suitable for modeling situations where large numbers of humans are present and each makes their own choice between many alternatives. This makes it easy to include individuality and see the impact on the overall system of the variations in different people's behaviors.

Applications of Agent-Based Simulation

Agent-based modeling can be viewed as a methodical advancement and generalization of microscopic modeling styles in object-oriented and discrete-event simulation. Agent-based simulation is

Table 2. Comparison of System Dynamics, Discrete-Event and Agent-Based Simulation

	Features	System dynamics	Discrete-event simulation	Agent-based simulation
T2:2	Overall approach	Abstract, state variables and equations that are solved to simulate behavior over time	Randomness associated with interconnected events leads to system behavior	Physical emulation of *agents* whose rules for behavior mirror the real world
T2:3	Mathematics	Calculus; numerical integration of different equations	Statistical distributions to model the increments of simulation clock	Logic, algorithms, and simple probabilities
T2:4	Representation	System represented as stocks and flows	System represented as queues and activities, schedules, processes, buffers	Autonomous, responsive and proactive agents which interact with each other to achieve their objectives
T2:5	Problem key	The understanding of the problem lies in analysis of causal feedback effects	Randomness associated with interconnected processes and events	Individual agent classes with the rules for their interaction
T2:6	Ease of communication	Very good for showing model structure and numerical results	True representation of system	Excellent for showing the behavior of individual entities
T2:7	Relationship	Interested in identification of nonlinear relationships	Relationships can be nonlinear but mostly are linear	Relationships are nonlinear
T2:8	Spatial relationship between entities	Spatial relationship is not represented because entities are aggregated	Distances between entities in the model cannot be calculated; discrete-event simulation model can take account of distance between entities and resources	Spatial relationship can be a key driver in the model. Individual agent behavior can be influenced by spatial relationship
T2:9	Accuracy of the model	Moderate in accuracy; the outcome of model is as learning laboratories	Owing to its heavy reliance on data, the model produces accurate, statistically valid models	Models are much more difficult to construct compared with discrete-event simulation models and can have accurate models
T2:10	Parameters	Model's parameters are affected feedbacks loops with the system	Parameters are set after intensive research on historical data	The paradigm carefully considers the definition of agents and specifies their behavioral rules in the simplest possible fashion
T2:11	Structure-determined performance	Based on the concept that performance of the model over time is determined by its structure	Based on the concept that performance of system over time is determined by randomness and by the internal structure of the system	Based on the concept that performance of system is the emergence of ordered structures independently of top-down planning
T2:12	Role of computer simulation	Computer simulations are used as learning laboratories that allow managers to run models in the gaming environment	Models are less used as learning tools for nontechnical people	The models are flexible; it is easy to add more agents to an agent-based model; a natural framework is provided for tuning the complexity of the agents.
T2:13	Computer animation	Computer simulation is limited to graphs and equations	With its computer animation capabilities where entities can be shown moving across the system, can help more in visual understanding of process flow	With its computer animation capabilities, can display visual world environment for understanding operation process

Note: Wakeland et al. (2004); Borshchev and Filippov (2004); Owen (2008).

typically applied in microscopic modeling of systems where common actions of autonomously deciding actors (people) are represented (Page et al. 2007).

Agent-based simulations can serve as artificial laboratories which will test ideas and hypotheses about phenomena which are not easy to explore in the real world. Crooks (2009) introduced a simulation and modeling system called *Second Life*, and demonstrated its usage for agent-based modeling, in particular illustrating the integration of symbolic models with iconic structures. Crooks made a basic three-dimensional (3D) agent-based pedestrian evacuation model which combined both symbolic and iconic style models into a single form. Agents not only interact with each other but also interact with their surrounding environment. Crooks (2009) created a building in an artificial world, populated it with artificial people, started a fire and watched what happened. Agent-based models are quite suited to such topics where, with the help of simulations, modelers can identify potential problems such as bottlenecks and test numerous scenarios such as the way various room configurations can impact on evacuation time.

However, *Second Life* has a lot of disadvantages which limit its capability for the creation of agent-based models. In addition, *Second Life* is not free for use like most open source ones. The *Second Life* visual environment is only a demonstration of agent-based modeling application. Agent classes and rules for their interactions cannot be built for their specific own purposes.

To have one's own agent classes and related rules, object-oriented programming techniques should be chosen to build agent-based models. The advanced computational technology helps populate large numbers of agents and calculate their interactions and emergence outcomes. In the last few years, the agent-based modeling community has developed several practical agent-based modeling toolkits that enable the development of agent-based applications. The toolkits have a variety of characteristics. Fig. 8 shows their capacity for modeling complex and large-scale applications compared with the ease of developing a model.

The most popular tools to assist agent-based studies are the object-oriented languages Java, *Repast* symphony toolkit, *NetLogo* toolkit, *Swarm* toolkit and *AnyLogic v6*. According to the specific application, an appropriate toolkit may be chosen (Table 3). It would need a myriad of programming work to build the visual simulation context (i.e., an airport terminal environment) in the *Repast* symphony toolkit before it can truly be implemented as an agent-based passenger flow simulation. *NetLogo* could be insufficient to model a large system owing to its comparative low modeling power. Comparing the *Swarm* toolkit and other software, *AnyLogic* is user-friendly and can be used to integrate agent-based concepts.

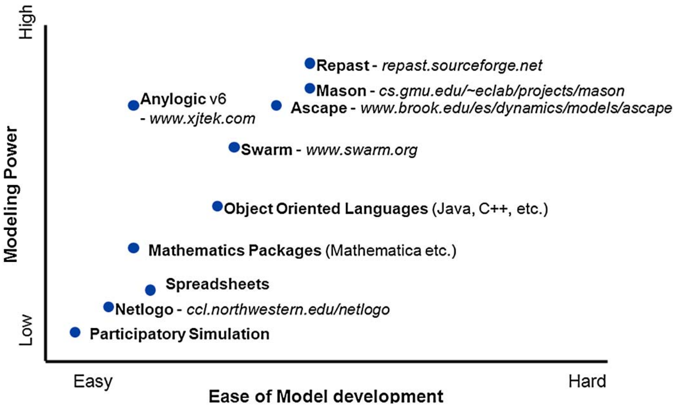


Fig. 8. Agent-based modelling software [data from Macal and North (2006)]

Any logic is used as the simulator platform to conduct modeling passengers flow in this thesis. *AnyLogic* is a multiparadigm/hybrid simulator capable of modeling systems as a combination of discrete-event, system dynamics and agent-based modeling. It is based on UML-RT and uses *hybrid state charts* to achieve this unique capability. It is based on Java and the models can also run on many other platforms. Any logic supports agent-based modeling and can be efficiently combined with other modeling approaches. *AnyLogic* has several embedded simulation libraries which can make building agent-based models easier. Its pedestrian library is convenient for setting up pedestrian walking in spatiotemporal circumstances.

Doing research on complex systems is a big challenge. However, it is becoming possible to take a more realistic view of these systems through agent-based modeling and simulation. Computational power is advancing rapidly, and such advances have made possible a growing number of agent-based applications in a variety of fields. Computing large-scale microsimulation models is becoming plausible at present. Furthermore, data are becoming organized into databases at finer levels of granularity. Microdata can now support microsimulations. The invention of relational databases indicates that data can now be organized into databases at microdata levels.

These findings can be used to improve design elements of pedestrian facilities and walking routes. Proper understanding of self-organization phenomena allows modelers to change the patterns of motion and their efficiency by suitable specification of the boundary conditions. For example, Helbing et al. (2005) used suitably located *obstacles* to stabilize flow patterns and to make them more fluid. The flow pattern of people would behave *back and shock waves* in queues and crowds because of the impatience of some persons. It was suggested that long waiting time can be avoided by increasing the diameters of routes. In addition, zigzag-shaped geometries and columns could reduce the pressure in panicking crowds, if properly designed and placed. So, efficiency and safety of built environments could be increased accordingly. Furthermore, through parallel simulation of the social force model on PC clusters, it becomes possible to evaluate mass events within airport terminals and railway stations. Pedestrian flows in extended urban areas can also be simulated (Batty et al. 2003; Helbing et al. 2004). This allows access not only to information about the attractiveness of certain locations for new shops, but also the impact of new buildings like theaters or malls on overall pedestrian flows.

Pedestrian Flow Simulation 1054

Measurement and Control of Pedestrian Interaction

Pedestrian interaction is the repulsive and attractive effect among pedestrians and between pedestrians with their environment. Because the movement quality of pedestrians can be improved by controlling the interaction between pedestrians, better pedestrian interaction is the objective of this approach.

Pedestrian interaction can be measured and controlled. Pedestrian flow performance is defined as the indicators to measure the interaction between pedestrians. The pedestrian interaction can be controlled by time, space and direction. Pedestrians may be allowed to wait for some time, or walk to a particular space (e.g., door) or right of way (e.g., walkway), or in certain directions. Case studies using microscopic simulation as reported by Helbing and Molnar (1998) and Burstedde et al. (2001) show that the flow performance of pedestrians in the intersection of pedestrian malls and doors could be improved by introducing some controls such as roundabouts or direction rules. More efficient pedestrian flow can even be reached with less space. Those simulations have rejected the linearity assumption of space and flow at the macroscopic level. Analytical models for microscopic pedestrian model have been developed by Henderson (1974) and Helbing (1992), but the numerical solution of the model is very difficult, and simulation is therefore favorable.

Therefore, microscopic pedestrian studies are needed to improve the quality of pedestrian movement. In microscopic pedestrian studies, every pedestrian is treated as an independent entity, and the behavior of pedestrian interaction is measured. It could be a third way of doing science besides deductive and inductive

Table 3. Comparison of Agent-Based Modelling Toolkits

Platform	Primary domain	License	Programming language	GIS capabilities	3D capabilities	Model power
NetLogo	Social and natural sciences	Free, not open source	NetLogo	Yes	Yes	Low
MATLAB	Simulation; programming; scientific and engineering math and computation; data analysis	Proprietary	Matrix-based data structures, m-language, and extensive catalogue of functions	N/A	Poor (SimuLink)	Moderate
Swarm	General purpose agent-based	General public license	Java	N/A	N/A	Moderate
Mason	General purpose; social complexity; physical modeling, abstract modeling, artificial intelligence/machine learning	Academic free (open source)	Java	N/A	N/A	High
Repast	Social sciences	Berkeley software distribution	Java (RepastS); Python (RepastPy);. Net, C++	Yes	Yes	High
Anylogic	Agent-based; distributed simulation	Proprietary	Java; UML-RT (unified modeling language)	Yes	Yes	High

reasoning (Macal and North 2005). There are a few research works which tried to construct agent reasoning framework:

The concept of motivations as the driving force that affects the reasoning of agents in satisfying their goals is considered as the underlying argument for agents to voluntarily comply with norms, and to voluntarily enter and remain in a society (López et al. 2006).

In the SMART agent framework (d'Inverno and Luck 2003):

- An attribute represents a perceivable feature of the agent's environment, which can be represented as a predicate or its negation.
- A particular state in the environment is described by a set of attributes.
- A goal represents situations that an agent wishes to bring about.
- Motivations are desires or preferences that affect the outcome of the reasoning intended to satisfy an agent's goals.
- Actions are discrete events that change the state of the environment when performed.

A model developer must identify, model and program these elements to create an agent-based model. The model should operate satisfactorily in a discrete formulation. Because decisions and movements in reality are being made in parallel in a continuous space-time framework, the errors generated by resorting to sequential decisions in a discrete or partially discrete framework should not be too gross. The model should be easy to upgrade to more detailed descriptions of behavior if necessary. Approximations of real behavior which are satisfactory in one context are not necessarily suitable for general use. Consequently, the basic model should be simple, but nevertheless relatively easy to modify or refine.

The operation of the simulation should be suitable for real-time graphical monitoring. Many potential users are more likely to be interested in *seeing* what conditions certain layouts produce rather than reading tables of figures describing them. The simulation is implemented at the level of the individual pedestrian under the hypothesis that if the behavior of individuals is modeled adequately, and the appropriate distribution of pedestrian types is employed, the behavior of the simulated pedestrians will be realistic. Further, by working at the level of the individual it is possible to collect data on individual travel times and diversions, and subsequently to analyze the variability between different types of pedestrian.

However, to simulate pedestrian flows at the level of the individual, it is necessary to be able to model the way in which pedestrians select their routes and move along them. The present model separates these two aspects of pedestrian behavior into independent submodels which can be treated sequentially. That is, the pedestrian selects a route or part of a route, and then endeavors to follow it as consistently as possible. This separation of pedestrian behavior into these two components permits the development of efficient mathematical criteria at later stages. Moreover, it is necessary to discuss the general principles of route selection so that the relationship between route selection and pedestrian interaction can be appreciated. Unless the relationship is understood, the criteria and behavior associated with pedestrians, although following their route, may seem too limited.

Pedestrian Flow Validation

In computer modeling and simulation, validation is the process of determining the degree to which a model or simulation is an accurate representation of the real world from the perspective of the intended uses of the model or simulation. Often there is a trade-off between increasing confidence in the level of accuracy of the models and the cost of data collection and effort required to validate the models (Barton-Aschman Associates and Cambridge Systematics 1997).

Model validation is a method of ensuring that the model replicates the observed conditions and produces reasonable forecasting results and to see whether there is an adequate agreement between a model and the system being modeled. The validation part concerns the determination of the numerical value of the parameters and the results of the simulation. Validation involves testing the model's predictive capabilities. Pedestrian flow models need to be able to replicate observed conditions within reason before being used to produce future forecasts. As urban areas and built environments are not identical, the credibility of the pedestrian flow process will depend largely on the ability of analysts to properly validate the procedure and models used.

A critical issue for pedestrian models is the validation of the model against real-world data. Because of many factors being involved in the simulation of individual pedestrians and the large set of parameters in pedestrian models, the validation of a pedestrian model is very difficult (Teknomo and Gerilla 2005). Only limited validations of pedestrian flow systems have been done. Lovas (1994) and Helbing and Molnar (1995) used simple observation methods to validate pedestrian flow. Blue and Adler (2001) validated a pedestrian multi-agent system by utilizing matching speeds with Highway Capacity Manual standards. Teknomo and Gerilla (2005) conducted sensitivity analysis of control variables and parameters of the pedestrian multi-agents model and applied an automatic validation method. All in all, validations for pedestrian flow models require deep understanding of the behavior of the factors and parameters.

The validation step ensures that the simulation model behaves as expected. The pedestrian flow model involves the issue of both space and time. Therefore, for pedestrian flow validation in general, individual pedestrian factors and model parameters all need to be considered. Typically, the radius of a pedestrian body is around 60 cm, and average speed is 1.34 m/s (Teknomo and Gerilla 2005). One way to inspect this behavior is the decline of the average speed as the density increases. According to Teknomo and Gerilla (2005), data can be gathered manually or through video of a specific location where pedestrians are crossing. Manually collecting pedestrian flow data requires hard work and always takes significant time. For video data collection, each camera captures real pedestrian flow in one area. Sample video data can be collected in a uniform time-period or instead through consecutively capturing a constant number of pedestrians. Moreover, an image processing method needs to be developed and to track pedestrians and record the number of pedestrians passing the area. Analysis needs to be done to generate related data, namely, the speed and number of pedestrians in an area. Once real-world data are obtained, all the statistics are used for validation with pedestrian flow modeling/simulation results in certain aspects, such as speed of overall flow, instantaneous occupancy by pedestrians at a specific area and routing phenomena.

Conclusions

Research interest in pedestrian dynamics spans the retail industry, emergency services, urban planners and other agencies. Macroscopic models of pedestrian movement simply take into account the predetermined pathways of pedestrians, such as corridors or vacant areas within built environments, and do not consider detailed interactions among pedestrians and building facilities. However, in fact, building facilities in general would occasionally divert the pedestrians' walking path, such as window displays that will attract certain pedestrians who are wandering around and looking for something interesting in a mall. Thus, macroscopic models are not well suited for the accurate prediction of pedestrian flow performance.

On the contrary, microscopic models have more general usage and consider detailed flow performance. Four major microscopic pedestrian flow models were addressed. The benefit-cost cellular model is limited by its physical representation and thus not convincing in its ability to solve all the relevant interaction issues, that is, walking speed, direction and avoidance with other pedestrians and obstacles. The magnetic and social force models have more variables with physical meaning and can better explain the behavior of pedestrians. The pedestrian flow model of Kholshevnikov (2008) demonstrates that the emotional state of persons towards their travel speed can be affected by pedestrian flow density. Because conventional studies are based on macroscopic aspects, the capabilities of microscopic aspects are not fully developed. Agent-based modeling is an important microscopic approach, which treats each individual as an independent agent with multiple traits.

Agent-based modeling was illustrated to demonstrate applications of modeling people walking at spatial scales and in city or urban areas. Agent-based modeling is able to study interactions among pedestrians and ambient environment objects. As computing technology advances, pedestrians are modeled more realistically, not simply as a dot or rectangle. The physical traits of a pedestrian agent and the function of interactions within crowds need to be modeled. Detailed physical interactions among pedestrians and building facilities are also expected to be clearly studied. In terms of the aspects of physiology and psychology, research opportunities exist for the physical interactions and route-choice decisions of pedestrians.

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